Finishing the Last Lap: Experimental Evidence on Strategies to Increase Attainment for Students Near College Completion

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Abstract

Nearly half of students who enter college do not graduate. The majority of efforts to increase college completion have focused on supporting students before or soon after they enter college, yet many students drop out after making significant progress towards their degree. In this paper, we report results from a multi-year, large-scale experimental intervention conducted across five states and 20 broad-access public colleges and universities to support students who are late in their college career but still at risk of not graduating. The intervention provided these "near-completer" students with personalized text messages that encouraged them to connect with campus-based academic and financial resources, reminded them of upcoming and important deadlines, and invited them to engage (via text) with campus-based advisors. We find little evidence that the message campaign affected academic performance or attainment in either the full sample or within individual higher education systems or student subgroups. The findings suggest low-cost nudge interventions may be insufficient for addressing barriers to completion among students who have made considerable academic progress. © 2022 by the Association for Public Policy Analysis and Management.

INTRODUCTION

College enrollment rates have increased steadily over the last several decades, yet the probability of degree attainment among enrollees has stagnated. Just over half of students who start college complete their degrees within six years of entry (Bound, Lovenheim, & Turner, 2010; Shapiro, Dundar, Wakhungu, et al., 2016). Low-income students and students of color are significantly less likely to graduate than their high-income and White peers; these disparities have only widened over time (Bailey & Dynarski, 2011; Chetty, Friedman, Saez, et al., 2020).

To date, most efforts to increase college completion rates have focused on supporting students before or soon after they enter college. For example, several interventions have focused on encouraging students to attend higher-quality colleges from which they are more likely to graduate, supporting students to apply for federal student aid, and helping students overcome procedural obstacles to matriculation that arise before students arrive on campus (Barr & Castleman, 2021; Bettinger et al., 2012; Castleman & Page, 2015; Hoxby & Turner, 2013). Colleges and universities have also devoted considerable attention to students' first-year experiences in college, with interventions ranging from structured learning and advising supports

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(e.g., CUNY ASAP), learning communities, and first-year seminars, to improving remediation policies for students who enter college academically underprepared (Bettinger & Long, 2009; Culver & Bowman, 2020; Martorell & McFarlin, 2011; Schnell & Doetkott, 2003; Scott-Clayton, Crosta, & Belfield, 2014; Scrivener, Weiss, Ratledge, et al., 2015; Visher, Weiss, Weissman, et al., 2012).

Evidence suggests that these strategies can increase the share of students that successfully navigate the transition to college and make progress toward their degree. However, many students who persist beyond the first year of college remain at substantial risk of withdrawing prior to earning their degree. More than 40 percent of college students who do not graduate leave after their second year of college (Bowen, Chingos, & McPherson, 2009; Shapiro, Dundar, Yuan, et al., 2014). Recent evidence also suggests that one in three dropouts complete at least three-quarters of the credits typically required to graduate before they withdraw (Mabel & Britton, 2018). Across the country, this translates into approximately 400,000 students per college entry cohort who have earned substantial credits but do not have a degree to show for it.[1]

A combination of limited support for more advanced students and novel challenges that arise as students approach completion contribute to these high rates of late withdrawal. The road to completion becomes increasingly self-directed as structured student support services taper off after the first year of college (Scott-Clayton, 2015). Students may therefore struggle to make and follow through on complicated decisions, such as determining which courses to take to fulfill their degree requirements, when academic advising is limited and often difficult to access. The nonmonetary costs of navigating a challenging environment alone may also be difficult for older students who lead busy lives and have limited networks of academic support outside of school.

In this paper, we present experimental evidence from a large-scale intervention, called Nudges to the Finish Line (N2FL), that we designed in close partnership with 20 colleges and universities to increase completion among students who had made significant progress towards their degree and were still actively enrolled in college.[2] We implemented N2FL in partnership with public higher education institutions in New York City, Virginia, Texas, Ohio, and Washington State during the 2016/2017 through 2018/2019 school years. We designed N2FL as a text message campaign that: (a) encouraged students to connect with campus-based academic and financial resources; (b) reminded them of upcoming and important deadlines; and (c) invited students to engage via text with dedicated college advising staff.[3] Students received approximately one message per week over the course of two to three semesters. The study sample includes 21,533 students across the 20 partner institutions.

Several recent papers have found null impacts from large-scale nudge campaigns that aimed to improve postsecondary outcomes (Avery, Castleman, Hurwitz, et al., 2020; Bird, Castleman, Denning, et al., 2021a; Gurantz et al., 2021; Page et al., 2019). The design of N2FL differed in important ways from these studies, which led us

[1] These estimates are based on results from Mabel and Britton (2018), who find that 14 percent of all degree-seeking students attending public colleges in Florida and Ohio completed three-quarters of the credits typically required for graduation but did not earn an associate or bachelor's degree. On average, those students enrolled in college for 3.2 years and paid $11,500 per year in out-of-pocket expenses (Horn & Paslov, 2014). Nationwide, state appropriations and grants also subsidize the cost of attending public colleges and universities by $10,000 per year on average (Schneider, 2010). Of the 15.5 million students enrolled in degree-seeking programs in the United States, this equates to approximately 2.2 million students who have earned substantial credits but no degree with substantial costs to individuals and to taxpayers.

[2] Students were eligible to participate if they had completed at least half of the credits typically required for associate or bachelor's degree attainment at two- and four-year colleges, respectively.

[3] Students did not have access to this type of text-based advising at two of the 20 institutions.

and partners to believe the intervention could effectively support higher rates of degree attainment among students with substantial credits. First, in order to foster trust and perceived legitimacy among students, we designed the campaign so that all messages were delivered by a specific advisor at students' college or university.[4] Second, the messages actively encouraged personal engagement and interaction (via text) between students and advisors; earlier text-based nudge campaigns that found positive impacts on students incorporated this interactive feature (Castleman & Page, 2015, 2016; Oreopoulos & Petronijevic, 2019). Third, by virtue of advanced students having less access to support than high school students or students early in college, we expected N2FL outreach to provide a more pronounced treatment contrast. Finally, to ensure the content was relevant to students at each college or university, we worked closely with advising staff at each institution to customize the message content, sequencing, and frequency of outreach to their institutional context.

That being said, most of the prior applications of nudges in postsecondary education have focused on encouraging students to complete discrete and consequential tasks, such as applying for financial aid. The efficacy of N2FL's nudges depended on students engaging in more sustained behavior change, such as meeting regularly with an advisor or taking advantage of course tutoring services. More recent studies have argued that nudges may be less effective when they are focused on promoting these types of ongoing behaviors (Oreopoulos & Petronijevic, 2019; Page, Lee, & Gelbach, 2020).

Results from a multi-cohort randomized trial of N2FL suggest that text-based nudges are not effective at addressing the barriers to completion experienced by students who have made substantial progress towards a degree. We find little evidence of effects on academic performance or attainment in the full sample and across colleges. Our statistical power is such that we can reject effects of 1.8 percentage points or larger on the probability of reenrollment or graduation. We also find no evidence of varying impacts of the N2FL nudges based on students' baseline predicted probability of dropout prior to earning a degree. We analyze numerous dimensions of treatment fidelity and the institutional context to investigate why N2FL may not have been effective. For instance, we explore whether impacts vary based on the rate at which college advisors responded to students' texts. We also investigate whether N2FL was differentially effective based on whether the college had parallel texting campaigns. None of these analyses reveals institutional contexts, advisor practices, or other dimensions of project implementation that are associated with heterogeneous treatment impacts.

Our paper makes several important contributions. Ours is the first paper of which we are aware to investigate whether interactive, text-based nudges can improve attainment among students who have made substantial progress towards a degree and who are still in college. Several interventions have attempted to increase reenrollment and success among students with substantial credits who had already withdrawn, with limited efficacy (Adelman, 2013; Ortagus, Tanner, & McFarlin, 2021).[5] Second, our paper shows that the limited efficacy of nudges in postsecondary education is not a function of the level of implementation or the lack of access to text-based advising, as prior papers have hypothesized (e.g., Bird, Castleman, Denning, et al., 2021a). We find null impacts even though the nudges were sent by colleges and universities with whom students had a direct connection and invited students

[4] This stands in contrast to recent ineffective nudge campaigns where messages came from a state or national organization with whom students had at best a tenuous relationship.
[5] For example, through Project Win-Win, a partnership between the Institute for Higher Education Policy and the State Higher Education Executive Officers, 60 postsecondary institutions attempted to re-engage former college-goers requiring nine or fewer credits to earn an associate degree (IHEP, 2013).

to connect with college advisors via text. Finally, by leveraging detailed data on the institutional context in which N2FL took place and data on treatment implementation and fidelity, we are able to investigate more deeply than prior papers factors that could contribute to the efficacy of nudge interventions in higher education.

The remainder of this paper is structured as follows. In the next section, we provide a brief discussion of the obstacles to completion that disadvantaged populations face at broad access institutions and elaborate on which barriers the N2FL intervention is designed to address. In the following section, we present details on the research design, including the participating schools, intervention components, study sample, randomization procedure, and empirical strategy. We then present results, and we conclude in the final section with a discussion of our findings and their implications.

OBSTACLES TO COLLEGE COMPLETION

A large body of evidence suggests that the costs to completing college are steep and may increase as students progress through school. Many students experience high time and effort costs to completion because they enter college academically unprepared (Bettinger, Boatman, & Long, 2013). Resource constraints at broad-access public institutions in the United States, where the majority of postsecondary students attend, have escalated those costs by creating a shortage of student supports at many institutions (Bound, Lovenheim, & Turner, 2010; Deming & Walters, 2017).

Resource deficiencies are an especially large impediment to student progress because the college environment at most broad-access institutions is complicated and difficult to navigate. For example, the volume of courses offered at open-enrollment institutions and the array of program requirements make it hard for students to know which courses to take in a given term to make efficient academic progress (Nodine, Jaeger, Venezia, et al., 2012; Schneider & Yin, 2011). With student-to-counselor ratios frequently exceeding 1,000:1, advising is also extremely limited, and institutional bureaucracies make it hard for students to access individualized assistance (Grubb, 2006; Scott-Clayton, 2015). According to survey research, one-third of community college students never use academic advising as a result, even though nearly half of students do not understand their graduation requirements or what courses count towards their degree (Center for Community College Student Engagement, 2015; Rosenbaum, Deil-Amen, & Person, 2006).

Within this isolated and confusing landscape, several studies find large effects from interventions that provide students entering college with enhanced mentoring, tutoring, and other supports (Angrist, Lang, & Oreopoulos, 2009; Bettinger & Baker, 2014; Castleman & Page, 2016; Clotfelter, Hemelt, & Ladd, 2016; Scrivener, Weiss, Ratledge, et al., 2015). However, because these supports are costly, institutions typically target resources to first-year students and the impacts of early interventions fade out over time (Rutschow, Cullinan, & Welbeck, 2012; Visher, Weiss, Weissman, et al., 2012). Completing complex tasks may therefore remain a formidable barrier for students as they continue to progress in school.

Furthermore, as students age and take on more responsibilities outside of school (Erisman & Steele, 2015; U.S. Department of Education, 2017), the attention to devote to difficult tasks may become increasingly limited and lead to more frequent oversight of important deadlines and higher psychic costs (e.g., mounting stress, anxiety, and impatience) when obstacles arise. All of these factors may contribute to short-sighted perceptions that the immediate costs to continuation exceed the unrealized future benefits of earning a degree (Cadena & Keys, 2015; Gurantz, 2015).[6]

[6] To inform our intervention design, Persistence Plus also conducted student focus groups at each institution participating in the pilot year during spring and summer 2016. The most common challenges

These factors also suggest that targeted interventions may be a cost-effective investment towards increasing degree attainment for students on the margin of completing college. On the other hand, if the costs to completion for late-stage students are primarily due to other factors, such as academic skill deficiencies that make it difficult for students to pass specific course requirements in their major, then nudge interventions may have little impact on academic progress and may motivate the need for more resource-intensive strategies to lower rates of late departure.

RESEARCH DESIGN

We partnered with a diverse array of broad-access, public two- and four-year institutions across the country to implement N2FL. All our partner institutions accept 75 percent or more of the applicants that apply. Sixty percent of students attending our partner institutions enrolled part-time, 32 percent received federal Pell Grants, and 50 percent were students of color. The average graduation rate within 150 percent of the expected time (e.g., six years for a four-year degree) reported by our partner institutions was 29 percent. Of the 20 institutions that participated in N2FL, three are community colleges and three are four-year colleges in the City University of New York system; seven are community colleges in the Virginia Community College System; three are community colleges in Texas; two are four-year public universities in the University of Texas system; and two are four-year public institutions in Ohio and Washington State. We pre-registered our evaluation of N2FL at the Open Science Framework.[7]

Eligibility Criteria and Sample

Degree-seeking students were eligible to participate in the study if they: (a) were actively enrolled, (b) had an active cell phone number on record with their institution, and (c) completed at least 50 percent of the credits typically required for degree completion prior to intervention launch.[8] We established broad eligibility criteria to examine heterogeneity in treatment effects by predicted risk of dropout.

Based on the eligibility criteria above and the size of enrollments at our partner institutions, we recruited 21,533 students to participate in the study. Of this experimental sample, we randomly assigned 13,826 to the treatment group and 7,727 to the control group. Students assigned to the control condition did not receive any text messages as part of the intervention but maintained access to the support structures typically available on their campus. However, as discussed above, outreach to students, especially upper-division students, is limited at many public colleges and universities. Therefore, the relevant counterfactual is that control group students did not receive personalized support unless they had the time, motivation, and awareness to seek it out.

In columns 2 and 3 of Table 1, we present summary statistics by treatment status for the students in the analytic sample. To examine the extent to which the sample reflects the population of undergraduates attending broad-access public institutions

students identified in those sessions were not knowing what steps to take to graduate and where to turn for help on campus when challenges arose.

7 The pre-registration for the study is available here: https://osf.io/xas3t/.

8 At two-year institutions, students in pursuit of associate degrees who had completed 30 or more college-level credits were eligible to participate. At four-year institutions, bachelor's degree-seeking students who had completed 60 or more college-level credits were eligible for the study. In practice, many students in the study sample were potentially closer to degree completion prior to intervention launch. One-third of students had completed at least 75 percent of the credits typically required for degree completion before outreach began.

Table 1. Pretreatment characteristics of experimental sample by treatment condition and summary statistics of nationally representative sample of undergraduates attending public two- and non-selective four-year institutions.

	(1)	(2)	(3) Experimental Sample	(4)
	NPSAS Sample	Treated Students	Control Students	T-C Difference
Male	0.438	0.433	0.442	0.000
Black	0.175	0.153	0.146	−0.001
Hispanic	0.220	0.223	0.208	−0.003
White	0.507	0.388	0.416	0.003
Race other	0.098	0.129	0.130	0.001
Race missing	0.000	0.108	0.100	−0.001
Age	27.10	21.58	21.39	0.102
Enrolled in public 2-year institution	0.781	0.522	0.467	0.000
Enrolled in public 4-year institution	0.219	0.478	0.533	0.000
Cumulative credits earned before intervention		61.76	65.98	−0.205
Share of credits earned before intervention		0.906	0.908	0.000
Transferred into current school		0.295	0.308	−0.006
Predicted risk of dropout		0.297	0.294	0.000
P-value on *F*-test for joint significance				.741
Number of Students:	58,410	13,826	7,727	21,553

Notes: The data in column 1 are from the National Postsecondary Student Aid Study of 2012 (NPSAS:12). Summary statistics in column 1 are calculated using survey sampling weights. The data in columns 2 through 4 are from partner institution administrative records. Means are reported in columns 2 and 3. Estimates of post-randomization balance are reported in column 4 from OLS/LPM models that include randomization block fixed effects.

nationally, we report (in column 1) analogous statistics for a nationally representative sample using data from the National Postsecondary Student Aid Study of 2012 (NPSAS:12). Finally, we report (in column 4) balance between the treatment and control experimental conditions.

Across both treatment and control groups, approximately 43 percent of students in the study sample were male, 50 percent were students of color, and the average age of students at the start of the intervention was 21.5 years. Approximately half of our experimental sample attended two-year institutions and half attended four-year institutions. Students had earned an average of 65 college-level credits and completed 91 percent of the credits they had attempted prior to the start of the intervention. Students in the study sample on average had a 30 percent chance of dropping out prior to earning their degree based on the predictive models we developed using historical data from partner institutions (see Appendix B for more details on these models).[9]

Our experimental sample is fairly representative of the national student population attending broad-access public institutions with respect to sex (44 percent of

[9] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

both samples are male) and racial/ethnic composition (49 percent of the population nationally is non-White versus 44.5 percent of students in the experimental sample for whom race/ethnicity is observed). Based on our institutional recruitment strategy, students attending four-year institutions are overrepresented in our sample (48 percent versus 22 percent nationally). As a result, on average, the students in our study are slightly younger than the typical enrollee at public broad-access institutions (21.6 years versus 27.1 years).

Intervention Design

N2FL consisted of a pilot phase (2016/2017 academic year) and a subsequent scale phase (2017/2018 and 2018/2019 academic years). Across both phases, 21 institutions participated in the study. Nine institutions participated in the pilot phase, eight of which also participated in the scale phase. We recruited an additional 12 institutions, for a total of 20, to participate during the scale phase. With the exception of one institution that only participated in the pilot phase, we estimate intervention impacts off a sample that includes participants in the pilot phase, scale phase, or both.[10] All nine pilot institutions used a text messaging model and platform called Persistence Plus, whereby both the automated messages and follow-up responses (to students who wrote back) were automated and personalized to students' use of keywords in their response.[11] Two of the pilot institutions, Ohio University and University of Washington–Tacoma, continued to use Persistence Plus during the scale phase.

The other 18 scale-phase institutions adopted an interactive two-way text messaging campaign that actively promoted opportunities for students to connect with advisors at their campus directly via text. Eligible students who were randomly assigned to treatment received approximately one pre-scheduled text message each week over the course of 2 to 3 semesters, depending on the institutional partner. These messages were sent automatically by the text messaging vendor, Signal Vine, according to a predetermined content schedule and delivery timeline that we developed collaboratively with advisors at each partner institution. We provide a sample of message content in Appendix A.[12]

We present, in Table C1, the start and end dates of messaging, the number of terms over which students were messaged, and student and advisor engagement statistics for each of our 20 scale phase institutions.[13] Messaging start and end dates depended on each institution's preference. Most institutions began messaging students during the 2018 calendar year. Students at most institutions received automated messages for 2 to 3 semesters, depending on each institution's preference.[14]

10 We excluded 500 students at one institution that only participated in the pilot phase because we observed a large initial enrollment difference between treated and control students at that campus. During the pilot phase, we randomized students in late summer before fall enrollments finalized, and message outreach began after classes started. The imbalance therefore occurred due to the timing of randomization, not as a result of message outreach, and would likely bias estimates of intervention impacts.

11 For example, during the spring term students who reported uncertainty about their remaining math requirements received the following messaging: "Last semester you were unsure whether you had any math requirements left to graduate. Were you able to get that sorted out?" Students who replied "Yes" then received the following response: "Fantastic! If you're currently taking any math courses remember that you can always visit the Math Lab in [on-campus location] for free tutoring."

12 All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

13 All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

14 Pilot phase institutions had six semesters of messaging: two semesters during the pilot phase and four semesters during the scale phase.

The topics and frequency of scheduled messages stayed fairly consistent across institutions. Messages were sent approximately once per week and prompted students to complete important tasks (e.g., register for the next semester's courses), encouraged them to use campus resources (e.g., tutoring centers, financial aid office), and addressed feelings of stress and anxiety (e.g., financial hardships). We worked with each partner institution to tailor pre-scheduled message content to their institutional context, such as inserting the name of campus-specific tutoring centers or modifying the tone to fit their student population.

The messages leveraged several key behavioral insights: (a) *Increase informational salience*: to simplify the process of accessing on-campus resources, one set of messages encouraged students to connect with campus-based academic and financial resources and provided them with specific contact and location information where assistance was available;[15] (b) *Promote implementation intentions*: a second set of messages reminded students of upcoming deadlines and encouraged them to make implementation plans that increase the likelihood of task completion (Milkman, Beshears, Choi, et al., 2011; Nickerson & Rogers, 2010);[16] (c) *Set positive social norms*: a third set of messages amplified descriptive informational norms to motivate action (Cialdini, 2016; McDonald & Crandall, 2015).[17]

One distinguishing feature of the N2FL intervention was the ability for students to write back to the scheduled messages with any questions or requests for help and get connected with campus advisors via text. Indeed, most scheduled messages encouraged students to text back by posing a final question designed to encourage student response and engagement. Each partner institution identified a specific advisor or staff team to monitor the text messaging inbox for student replies and to respond to students' questions or requests for assistance.

Staffing models varied across institutions: Some institutions elected to use professional or faculty advisors, while others appointed general staff (e.g., administrative assistants) to staff the messaging inbox and reply to students who texted in. The language of scheduled messages was modified to match the nature and scope of the designated staff's role. Specifically, institutions whose professional advisors had the capacity to support students directly (e.g., choosing which courses to register for or filling out the FAFSA) sent automated messages that offered direct assistance. In contrast, institutions that used a general administrative assistant offered assistance with connecting with the appropriate resources. A summary of the four primary staffing models that emerged can be found in Table C2.[18]

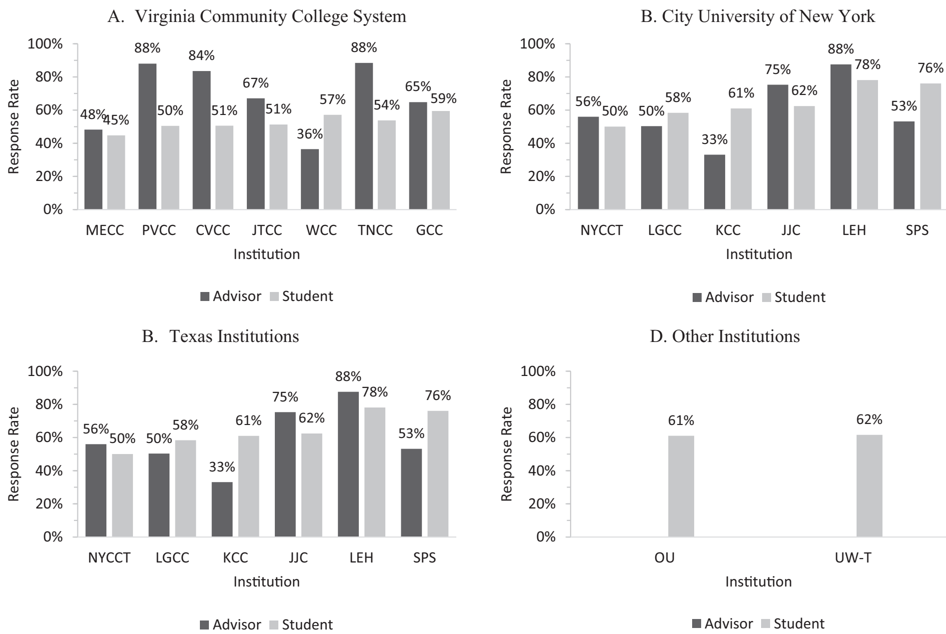
As we also show in Figure 1, message engagement rates varied substantially among both students and advisors across institutions. Student response rates were generally high across institutions, with approximately half or more of students responding at all institutions. That being said, institutional-level student response rates ranged from a low of 44 percent at Blinn College (Texas) to a high of 78 percent at Lehman College (CUNY). The average institution-level student response rate was 58 percent. Advisor response rates (to messages sent by students) also tended to be quite high, though there was more heterogeneity in institution-level advisor

[15] For example, the following message encouraged students to use tutoring resources: "Hi [student name], using the [name of campus tutoring center] can help you do well on midterms & boost your grades. Can I help connect you?"

[16] For example: "Hi [student name], Summer and Fall 2019 registration opens today. Don't miss your chance to secure a seat in the courses you need to graduate. What day do you plan to register?"

[17] For example: "Hi! Did you know 580,000+ New Yorkers filed FAFSA by this day last year? Join your peers and visit FAFSA.gov now to get the most aid." Some messages embedded infographics to reinforce the call to action and increase the salience of relevant information.

[18] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.



Notes: Student response rates are averaged based on cohort sample size at institutions with multiple intervention waves. Advisor response rates are averaged across cohorts and are not available for the fall 2016 intervention wave. Advisor response rates are not reported for Ohio University and the University of Washington–Tacoma because responses were automated at those institutions.

Figure 1. Engagement Statistics for Students and Advisors at Partner Institutions by System.

response rates than for student response rates: advisor response rates ranged from as low as 33 percent at Kingsborough Community College (CUNY) to a high of 88 percent at Thomas Nelson Community College (VCCS). Because higher or lower advisor response rates affected a key design component of the intervention (the availability of advising via text), we investigate whether this feature of institutional heterogeneity was correlated with N2FL efficacy.

Data and Measures

The data for this study consist of student-level administrative records maintained and provided by our institutional partners for both study participants and previous cohorts of students. The specific data elements vary across schools due to availability, but in general we observe baseline demographic and academic measures (e.g., gender, race, high school GPA, and college entrance exams, etc.) and term-by-term records of students' financial aid receipt, enrollment intensity (e.g., credits attempted), academic performance (e.g., credits completed, term, and cumulative GPA, etc.), and degree receipt. Most of our partner institutions also routinely collect enrollment and degree information from the National Student Clearinghouse (NSC) on previously enrolled students. We also relied on NSC data when they were available to capture transfer, enrollment, and degree information at non-participating institutions.

We use these data in three ways. First, we used the historical data provided by each institution to develop school-specific dropout prediction models. We present details

about the model construction process in Appendix B and report descriptive statistics of the study sample by tercile of predicted dropout risk in Table C3. Second, we use the data to assess whether students randomly assigned to the treatment and control conditions appear to be equivalent in expectation on observable and unobservable dimensions. Third, we use the data to evaluate the impact of the intervention on students' academic progress spanning different time horizons. In our main tables, we focus on impacts within four terms of the start of the intervention—the longest time horizon we can observe for all institutions.[19] In appendices, we report impacts of the intervention for the subset of earlier-participating interventions for which we can observe outcomes six terms after the start of the intervention.[20] We report on four primary outcome measures over these time horizons: whether students reenrolled or graduated, the cumulative number of credits earned following intervention, whether students graduated, and for students attending community colleges, whether they transferred to a four-year institution.

Randomization Procedure and Baseline Equivalence

To investigate whether impacts of message outreach varied with predicted risk of dropout, we randomly assigned students to receive message outreach using a block randomization procedure that afforded greater statistical power to examine evidence for heterogeneity of treatment effects.[21] We implemented this procedure by predicting the probability of dropout for currently enrolled students using the dropout models we developed. The models include a robust set of covariates correlated with whether students drop out before earning a degree, including: (a) fixed student attributes and time-variant measures before students completed one-half of the credits typically required for graduation, such as age, assignment to remediation status, and whether the student temporarily dropped out before completing one-half of their required credits to graduate; (b) measures of academic performance and financial aid receipt in the term students completed one-half of their credit requirements, such as attempted credits, cumulative GPA, and the cumulative proportion of attempted credits that were earned; and (c) measures of enrollment experiences and financial aid receipt after surpassing the one-half credit threshold analogous to those captured in (a) above. The model effectively differentiated between late dropouts and non-late dropouts in the historical samples: the probability that a randomly chosen late dropout was assigned a higher risk rating than a randomly chosen student who did not drop out ranged from 0.75 to 0.875 across the models. We describe the prediction models we developed more fully in Appendix B.

Within each institution, we then ranked students by dropout risk and randomly assigned students with similar probabilities of dropout to either the treatment or control conditions. At most institutions, we randomly assigned students to one of three treatment arms: a control condition and two variants of the treatment group, one of which received a set of messages focused more on academic barriers and another that received a set of messages tailored more to address financial obstacles (though students in both groups received messages about both academic and financial barriers and resources). However, in all analyses, we aggregate treated students

[19] One of the institutions only provided data through three terms following the intervention. To preserve our sample, we include this institution's students in our main tables. Results are robust to excluding this institution as well.

[20] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

[21] In our study proposal to the Institute of Education Sciences, we proposed to examine heterogeneity on this student background dimension alone. We therefore designed our study with this analysis in mind.

into a pooled treatment group because we do not observe evidence of differential effects by variant of message outreach.[22]

In column 4 of Table 1, we show that random assignment appears to have created equivalent groups of students in the treatment and control conditions. In both tests of equivalence on individual covariates and in our test for joint equivalence across all covariates, we fail to detect any significant differences between treatment and control students.[23] And as we show in Tables C4 through C6, the treatment and control groups are also well-balanced within each of our three higher education system partners (CUNY, THECB, and VCCS).

Empirical Strategy

To evaluate the effects of message outreach on academic progress and performance, we estimate intent-to-treat (ITT) models of the following form using ordinary least squares or linear probability models:

$$y_{ib} = \alpha + \beta T_{ib} + \delta_b + \zeta X_{ib} + \varepsilon_{ib}, \tag{1}$$

where Y_{ib} is one of the four academic outcomes described above for student i in randomization block b. T_{ib} is the treatment indicator set to one for students assigned to receive text-message support and zero otherwise. δ_b denotes randomization block fixed effects, which are groupings of students within each institution assigned a similar probability of dropout by the prediction models we developed for each college.[24] The coefficient of interest in this model is β, which represents the causal estimate of being assigned to receive text-based outreach. The set of student-level covariates (X_{ib}) is comprised of indicators for sex, race/ethnicity (Black, Hispanic, Other, and Missing Race), number of credits earned prior to the intervention, percent of attempted credits earned prior to the intervention, and whether the student had ever transferred prior to the intervention. We do not include campus fixed effects in the model, as time-invariant differences across campuses are already controlled for through the block dummies. ε_{ib} is a student-specific random error term, and in all results we report robust standard errors that allow for heteroskedasticity in the error term.

We examine heterogeneity of treatment effects by dropout risk by estimating models of the following form:

$$y_{ibk} = \sum_{k=1}^{3} \beta'_k (T_{ib} * DR_{ibk}) + \delta'_b + \zeta\, \prime^{X_{ib}} + \varepsilon\prime_{ib}, \tag{2}$$

where, as before, i and b respectively index students and blocks, and DR_{ibk} is an indicator for whether a student's predicted probability of dropout is in tercile k. All

22 Spillovers are unlikely in our context because the substantial majority of institutions in our experimental sample are large broad-access institutions that enroll primarily commuting populations. As a result, the probability that students in the study sample interact with each other on a regular basis is lower than is expected among students at smaller and primarily residential institutions.

23 Because the covariates we use to test for treatment balance are also used to generate the dropout risk predictions and construct the blocks in our randomization, we would mechanically not expect much variation between treatment and control groups on these covariates. This is not a concern, however, given that a large sample randomization is expected to result in statistically-equivalent groups on both observable and unobservable dimensions. Indeed, when we estimate models with no controls included, the results are very similar to those we estimate with covariates in the model (results available upon request).

24 Specifically, within each institution-by-intervention wave, we rank ordered students by their predicted probability of dropout and then used a nearest-neighbor approach to construct the randomization blocks. We constructed 2,534 blocks in total. The average block in the study sample includes 8.5 students.

Table 2. Estimates of intervention effects on academic outcomes.

	(1) Re-Enrolled or Graduated	(2) Number of Credits Accumulated	(3) Graduated	(4) Transferred to Four-Year
Four Term Outcomes:				
Treatment Impact	.0059	.421	−.0027	−.008
	(0.006)	(0.263)	(0.006)	(0.009)
Control Mean	.762	34.823	.591	.459
Observations	21,553	21,553	21,553	10,534
Six Term Outcomes:				
Treatment Impact	−.0036	.088	−.0065	−.011
	(0.007)	(0.416)	(0.007)	(0.012)
Control Mean	.815	42.623	.755	.526
Observations	12,879	12,879	12,879	6,788

Notes: Estimates are from OLS/LPM models that include randomization block fixed effects and the following pretreatment covariates: indicators for sex, race/ethnicity (Black, Hispanic, Other, and Missing Race), and transfer status at the start of fall 2016, as well as continuous measures of cumulative credits completed, and the fraction of total credits attempted that were earned at the start of the intervention. Robust standard errors are reported in parentheses. Column 4 only includes students at 2-year colleges.

other terms in the model are defined as above. This specification allows for estimation of treatment effects separately by tercile of predicted dropout risk, whereby tercile one categorizes students with low relative risk of dropout, tercile two captures students with medium risk of dropout, and tercile three denotes students with high predicted risk of dropout according to the college-specific dropout prediction models we developed using historical data from each institution.[25]

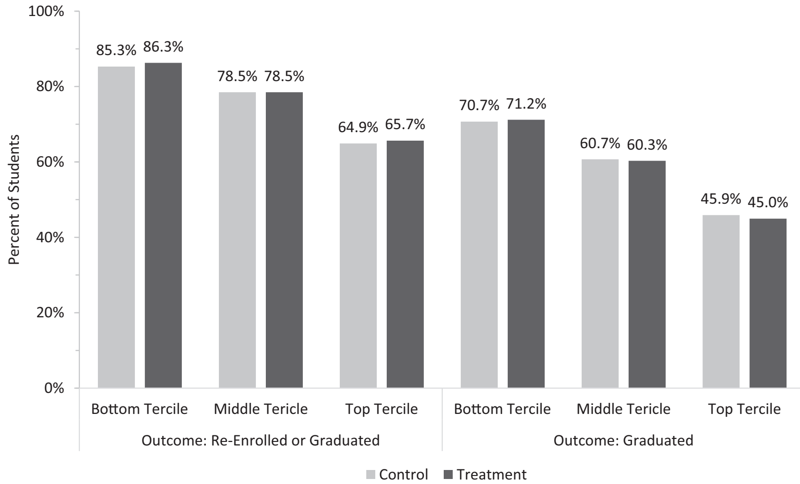
Finally, we investigate additional sources of potential heterogeneity in the impacts of N2FL in several exploratory analyses: by participating higher education system; by institutional staffing levels; and by whether institutions had ongoing texting campaigns in parallel to N2FL. We conduct these analyses by adding appropriate interaction terms to equation (1), but the results are unchanged if we instead conduct these analyses within each subsample.

RESULTS

Overall Impacts

In the top panel of Table 2, we present estimates of N2FL's impact on our primary outcomes of interest, measured for four terms following the start of the intervention at each institution. Across experimental conditions, most students (76.2 percent) reenrolled or graduated within four terms, and the N2FL interactive text messages did not significantly increase reenrollment or graduation rates. We can rule out impacts of 1.8 percentage points or larger on the probability of reenrollment or graduation. We similarly do not observe impacts of the treatment on the number of credits students accumulated. Likewise, when we investigate impacts of N2FL on degree

[25] Our estimates of heterogeneous impacts by baseline risk are robust to whether we group students into above- versus below-median groups, quartiles, or use a continuous measure of baseline risk.



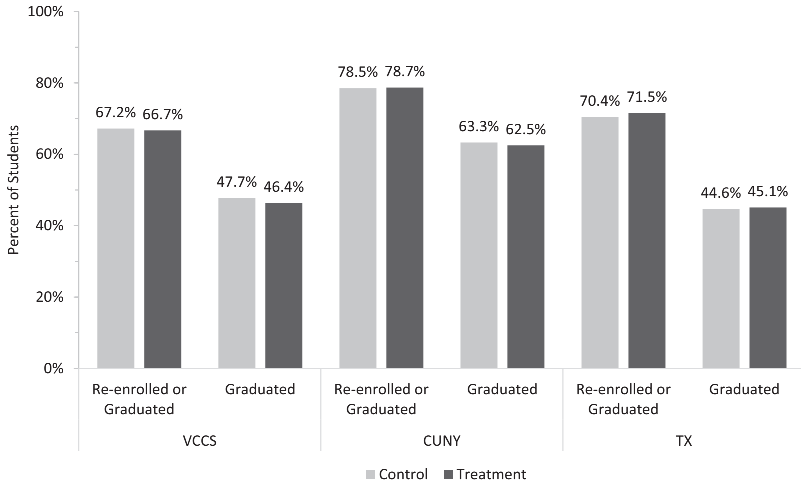
Notes: None of the treatment-control contrasts are statistically significant at the 10 percent level. Estimates are from OLS/LPM models that include risk rating, randomization block fixed effects, and the following pretreatment covariates: indicators for sex, race/ethnicity (Black, Hispanic, Other, and Missing Race), and transfer status at the start of fall 2016, as well as continuous measures of cumulative credits completed, and the fraction of total credits attempted that were earned at the start of the intervention. Risk ratings terciles are defined within an institution.

Figure 2. Estimates of Intervention Effects on the Probability of Re-Enrollment/Graduation Four Terms Following Intervention Launch by Tercile of Dropout Risk.

attainment alone, we also find no significant effects. Fifty-nine percent of the control group completed their degree within four terms, and we can rule out treatment impacts of 0.9 percentage points or larger. Among students at two-year institutions, we find no impact of N2FL on transfer to four-year institutions and we can rule out impacts of 1.0 percentage points or larger. Finally, in the bottom panel of Table 2, we show that there are similarly no effects of N2FL within six terms of the intervention for the subset of institutions for whom we can observe outcomes over that time frame. None of our estimates is significant, and if we were to apply multiplicity adjustments given the number of estimated impacts (here and throughout the paper), it would only further accentuate our lack of identification of significant impacts.

Impacts by Predicted Baseline Risk of Withdrawal

In Figure 2, we present heterogeneous impacts of N2FL on the probability of reenrollment or graduation and the probability of graduation alone four terms following the start of the intervention by tercile of predicted risk of withdrawal. As expected, we observe the highest rates of reenrollment or completion and degree attainment among students in the bottom tercile of risk. For instance, 70.7 percent of students in the control group in the bottom tercile earned a degree within four terms, compared with 45.9 percent of control students in the top tercile. Once again, we do not observe significant impacts of N2FL across any of the risk terciles on any of the primary outcomes, and in all cases can rule out even moderate treatment effects. In Table C7, we show that the null effects of N2FL across the distribution of predicted risk holds across other academic outcomes (i.e., credit accumulation and transfer among two-year enrollees) both four and six terms following intervention launch.



Notes: None of the treatment-control contrasts are statistically significant at the 10 percent level. Estimates are from OLS/LPM models that include risk rating, randomization block fixed effects, and the following pretreatment covariates: indicators for sex, race/ethnicity (Black, Hispanic, Other, and Missing Race), and transfer status at the start of fall 2016, as well as continuous measures of cumulative credits completed, and the fraction of total credits attempted that were earned at the start of the intervention.

Figure 3. Estimates of Intervention Effects on the Probability of Re-Enrollment/ Graduation Four Terms Following Intervention Launch by System.

Impacts by Higher Education System

We implemented N2FL across five states, with most institutions participating in one of three higher education systems: the City University of New York (CUNY), the Texas Higher Education Coordinating Board (THECB), and the Virginia Community College System (VCCS). These systems differ in their governance structure, public expenditures in higher education, institutional context, and student composition, so it is possible the impacts of N2FL would vary across systems. We investigated whether this is the case and display the results in Figure 3. As with the absence of heterogeneity by predicted risk, we find no evidence of impacts of N2FL on the probability of reenrollment/graduation or graduation alone four terms post-launch across any of the three higher education systems, and we can rule out the possibility of moderately-sized effects. We similarly do not find significant impacts by system on other academic outcomes and time horizons, as we show in Tables C8 and C9. We further show in Table C10 that the impacts of N2FL do not vary by predicted baseline risk within each higher education system. Finally, as we show in Table C11, the impacts of N2FL do not vary across two- and four-year institutions in the aggregate.[26]

Mechanisms

While we maintained a consistent core of scheduled message content across institutional partners, by virtue of working with 20 institutions, there were still potentially

26 All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

important differences in treatment implementation and institutional context that could lead to differences in N2FL efficacy. For instance, as we describe above, institutions varied in whether the staff member responding to student messages was a dedicated professional advisor, part of a team of advisors, or a non-advisor staff member who made connections to other advisors on campus. Institutions also varied in their overall level of advising support (which we proxy for using the advisor:student ratio), whether institutions required students to meet with academic advisors, and whether they had other texting campaigns operating in parallel with N2FL.

In Table C12, we investigate whether treatment efficacy varied based on any of these factors. We treat these investigations as exploratory since we are underpowered to detect impacts across numerous subgroups. Nonetheless, we fail to find any significant differences in N2FL efficacy by whether institutions used professional advisors, a team of advisors, a staff "connector," or in the case of two institutions, automated responses (Table C12, panel A). Nor do we find significant differences by whether institutions had larger or smaller advisor:student caseloads, required students to meet with advisors, or had parallel texting campaigns in place (Table C12, panel B).

Finally, as we describe above, we observed meaningful heterogeneity in advisor response rates across campuses. In Figure C1, we investigate whether the impacts of N2FL varied by advisor responsiveness to text messages students sent in response to scheduled outreach they received. Figure C1 plots treatment effects on our primary outcomes four terms post-intervention by quartile of advisor responsiveness.[27] We find no evidence of N2FL impacts on any of the main outcomes across the distribution of advisor responsiveness; furthermore, the confidence intervals of the effect estimate by quartile of advisor responsiveness overlap considerably. We conclude that N2FL had no impact on the likelihood of college persistence or degree completion, even among students paired with highly responsive and engaged advisors.

DISCUSSION AND CONCLUSIONS

Many college students within reach of graduation remain at risk of dropping out before they earn a degree. Although leaving without a degree may be a rational human capital investment decision for some, reducing late dropout is likely to benefit many near-completers, given the prevalence of the phenomenon and the high returns to degree completion for most college enrollees. We developed the N2FL intervention to examine if text-based outreach offers a scalable solution to support students at risk of late dropout while they remain enrolled in college. To our knowledge, previous interventions targeted to this population have strictly attempted to re-engage individuals after they have already withdrawn from school. The findings in this study provide strong evidence that low-touch interventions such as text-based outreach may not be an effective policy tool to reduce the incidence of late dropout from college. We estimate null impacts on persistence and completion in the overall sample, separately by students' baseline predicted risk of dropout, and across numerous dimensions of treatment fidelity and institutional context.

[27] The within-quartile outcome means for panel A are: Q1 = 75.6 percent; Q2 = 65.8 percent; Q3 = 75.1 percent; and Q4 = 74.2 percent. The within-quartile outcome means for panel B are: Q1 = 29.9; Q2 = 29.4; Q3 = 31.0; and Q4 = 24.2. The within-quartile outcome means for panel C are: Q1 = 58.5 percent; Q2 = 48.4 percent; Q3 = 60 percent; and Q4 = 42.0 percent. All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

The most immediate question is what explains the null impacts of N2FL. Our findings are consistent with several other recent nudge interventions in the education arena that have not scaled successfully (Bergman, Denning, & Manoli, 2019; Bird, Castleman, Denning, et al., 2021a; Gurantz, Howell, Hurwitz, et al., 2021). However, unlike N2FL, those interventions relied on messages delivered from organizations with which students did not have close, preexisting connections, leaving open the possibility that the efficacy of outreach campaigns requires participation of local entities that students trust. We find null impacts in this study despite partnering with institutions to design message content and sequencing, sending all messages from a specific advisor at the students' institution, and encouraging students and advisors to interact in real-time using two-way texting capabilities. The findings in this study therefore suggest that nudging at scale in postsecondary education is often not effective for other reasons.

We posit three alternative explanations for the null findings in this study. One possibility is that the messages were not salient enough to students to foster meaningful engagement with advisors on campus. Text-based outreach has become increasingly widespread over the past decade and colleges must compete more in recent years for the attention of students. Although we observed high student and advisor response rates in N2FL overall, we cannot rule out that college students may have reached a point of text message saturation, such that the efficacy of outreach campaigns launched five or 10 years ago will be more limited today.

Alternatively, because N2FL relied on the existing advising infrastructure of colleges and universities to engage with students, it is possible that the intervention asked too much of college staff with large caseloads and competing demands. This may be especially true in the context of upper-division students at risk of dropout, who may face acute academic and financial barriers that require more intensive assistance than two-way texting or traditional models of advising can provide (Mabel & Britton, 2018; Ortagus, Skinner & Tanner, 2020). The intensity of support at-risk students need may also explain the success of more resource-intensive interventions in college, such as one-on-one coaching programs (Bettinger & Baker, 2014; Oreopoulos & Petronijevic, 2017), which often have low student-coach caseloads and augment, rather than depend on, the traditional advising capacity of colleges. A third possibility is that N2FL may have engaged students too late into their college careers. As evident from the promising impacts of comprehensive college support interventions (Dawson, Kearney & Sullivan, 2020; Evans, Kearney, Perry, et al., 2020; Weiss, Ratledge, Sommo, et al., 2019), there may be important benefits to programs that engage students throughout their college career. If that is the case, then upper-division students at risk of dropout may benefit most from interventions that begin earlier and offer continuous support.

Although we are unable to pin down the precise reason(s) why N2FL produced null impacts, our findings are clear that college students at risk of late dropout likely require higher-touch intervention. Yet the reality is that high-touch interventions are expensive and many colleges, especially broad-access institutions that serve most students at risk of late dropout, operate on tight budgets. Helping more college students cross the finish line will require institutions to target resources to at-risk students who stand to benefit most. We embedded predictive modeling into the design of N2FL to help colleges identify which students experienced the largest gains from message outreach. While we find no impacts of message outreach on persistence and completion across the distribution of predicted baseline risk, the null effects found in this study do not necessarily reflect that predictive models convey limited utility for colleges. At the same time, recent research demonstrates that predictive models do not perform equally well for all student subgroups and that the specific modeling strategy used in predictive analytics can result in different student risk assignments (Bird, Castleman, Mabel, et al., 2021b). Additional research is needed

to critically investigate whether the use of predictive analytics in higher education leads to more effective, efficient, and fair targeting of students for success-oriented interventions.

Further research is also needed to determine if more intensive student support interventions that have proven effective in other contexts can lower rates of late dropout from college. To maximize the cost-effectiveness of those strategies, we encourage researchers to embed predictive analytics into future research, as we have done in this study, to help policymakers and college leaders better distinguish between marginal and inframarginal students. We believe this is the most feasible strategy for reconciling the tension between the resource-intensive supports that many college students appear to need and the resource-constrained environments in which most higher education institutions operate.

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